14.310x Flipped Classroom materials

—— —-

rduranl

Course Guide

14.310x Flipped Classroom
Week 1 Instructions

Some title

Checklist

- ☐ Complete the Intro to R interactive course from the `Swirl` package[1] (Requirement)
- ☐ Watch the Getting started with Google Colab notebooks video tutorial (Requirement)
- ☐ Create or set up a personal Google account
  (you must be able to use Drive and Colab). (Requirement)
- ☐ Create your first Colab notebook (Session 1)
- ☐ Complete Coding Lab 1. (Session 1)
- ☐ Complete Coding Lab 2 (Session 2)

C.1.0

Your first Colab notebook

Instructions: Read and follow the steps below **before proceeding with the activity**. After reading the instructions, access the notebook link and complete the exercises in Colab. This is an individual task, but you will collaborate on the final question.

Notebook: Your first Colab notebook

[1]**Module 1 > Introduction to R** in the online component of the course.

We will cover the essentials of working with Jupyter Notebooks on Google Colab — this resource will be an important tool throughout. Before you can begin working on the coding labs in Colab, make sure to:

- **Create or use a personal Google account**. While it is possible for you to download the Jupyter Notebooks we will work on, and manage them locally in your own machine, we strongly advise you to work on Colab since it will make it easier for your classmates and the instructor to interact with your work when needed. Colab has many features Google Drive already offers: comments, real-time colaboration in the same document or folder, etc.
- **Save the shared notebooks and documents to your own drive.** The notebooks you will have access to are read-only; in order to work on them you will have to copy them to your drive. It is recommended that you maintain a per-week structure in your folders as this will make it easier to follow instructions, especially when reading files or collaborating with others. To save the notebook to your Drive, go to the File menu: `File > Save a copy in Drive`.
- **(When creating a new notebook) Change Colab Notebook's runtime type to R.** By default, when you create a new notebook in Colab, the virtual machine Colab sets up for you is a `Python` installation. This means all the cells in the notebook will only recognize and run `Python` syntax or commands. To switch to an `R` language setup:
  1. Open the notebook menu and go to `Runtime > Change runtime type`.
     - Or click the toggle in the upper-right corner (as shown below) and select `Change runtime type`
  2. In the dropdown labeled `Runtime type`, select `R`.
  3. Click `Save`.

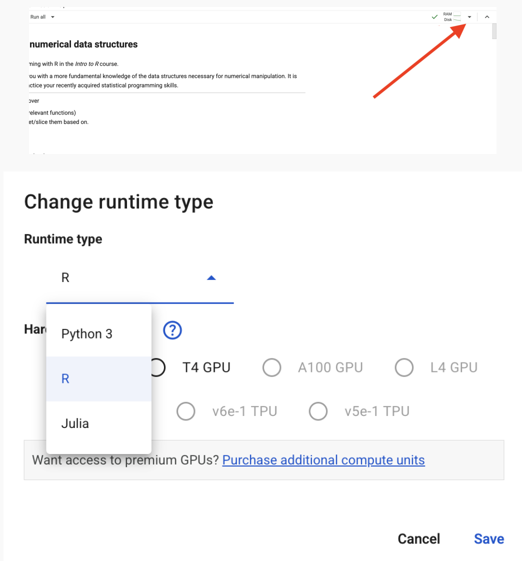


Fig. Changing the runtime type

You may now create your first Colab notebook

C.1.1

Coding Lab 1— Numeric data structures in R

Instructions: Work individually. Solve all exercises in the corresponding Colab notebook. Record your answers and/or code in your copy of the notebook.

Notebook: Coding Lab 1

Submit your work in the format required by the instructor.

C.1.2

Coding Lab 2 — Data manipulation with `dplyr`

Instructions: Work individually. Solve all exercises (sections 0 to 3) in the corresponding Colab notebook; record your answers and/or code in your own copy.

Notebook: Coding Lab 2

Optional **Section 4** allows work in pairs or teams of 3.

Upon completion, submit your work in the format required by the instructor.

14.310x Flipped Classroom
Week 2 Instructions

Some title

Checklist

- ☐ Complete the ADVANCED R interactive course from the `Swirl` package and watch the `ggplot` tutorial[2] (Requirement)
- ☐ Watch the **Import Data** tutorial[3] (Requirement)
- ☐ Read the note on importing `aiwars` and other datasets (Requirement)
- ☐ Complete Coding Lab 3 (Session 1)
- ☐ Complete Guided Case 2.3 (Session 2)

Importing `aiwars` and other datasets

Depending on flipped classroom logistics of your group, your access to the sessions' assets (datasets, figures, scripts, etc.) will come in one of two forms:

- **Through a direct URL** for instance, the original `aiwars.csv` dataset lives directly in this URL:
  `https://docs.google.com/spreadsheets/d/1NeZZWI2fT71M9QD8zjnz817T1B3XBM6lolqArSe9CwQ/export?format=csv`
- **Your instructor will provide them to you privately** and they will either:
  - Share them via a URL similar to the one above.
  - Share the files through other means.

[2] **Module 2 > R Course and R Tutorial: ggplot** in the online component of the course.
[3] **Module 3 > R Tutorials: Basic Functions** in the online component of the course.

As they may want to slightly modify the original files for grading purposes, or have any other goal in mind.

If a dataset's URL is provided, you can read the data directly into R with the URL and the appropriate reading function; simply provide the URL as the path. For instance, `aiwars` is in `.csv` format:

```
URL_aiwars <- "https://docs.google.com/spreadsheets/d...."

aiwars <- read.csv(URL_aiwars)
```

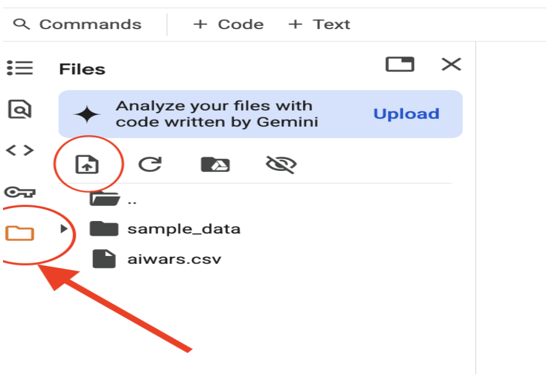
And similarly for other formats. Suppose we had a single Excel sheet:

```
install.packages("readxl")
library(readxl)

URL_aiwars_xl <- "https://...some-URL"

aiwars <- read_excel(URL_aiwars_xl)
```

If the file is shared in any other way, we will first need to upload it to the virtual machine's disk in Colab and read it from there, providing the `path` to it — as you would do if you were reading data to R in your own computer. To upload a file in Colab, click the folder icon in the leftmost menu bar, as shown in the screenshot. Then click the upload icon (circled in red); as you can see, we already uploaded the file.



Once uploaded the file can be read as a if in your machine:

```
aiwars <- read.csv("aiwars.csv")
```

Important: Colab runtime limitations

While your Colab notebook — including all code cells, text, and outputs — will remain saved, the underlying *runtime* (i.e., the virtual machine that executes your code) is temporary. After a period of inactivity or when a time limit is reached, the runtime will automatically disconnect.

When this happens:

  - All variables and objects stored in memory (e.g., your R data frames, models, vectors) will be lost.
  - Any files you uploaded manually will be erased.

When reconnecting, a fresh virtual machine will be started, and you'll have to re-run your code, and re-upload any needed files. Disconnects may happen occasionally as you work in off-notebook tasks; re-reading or re-uploading files should not take over 30 seconds.

Coding exercises in case studies

Throughout the course, the case studies you will work on contain a mix of conceptual and coding questions. To simplify your workflow, all the questions where you're required to write code are specially labeled. They appear in this format:

Question 5. [2.3] calculate the probability of event A...

The small icon signals that the question requires coding. The number inside the brackets (2.3 in this example) is a numbering **within the Session's dedicated Colab notebook**, which will often be different from the overall question number for the activity.

Further, if you click on the orange icon, it will take you directly to the question's cell within the Notebook by opening a new browser tab – remember you must work on your own copy of the notebook. These links are simply provided as a convenience to help you locate and visualize the relevant task quickly.

Apart from being the place where you are expected to code your answers, the corresponding cell usually includes a placeholder for your code, often accompanied by additional hints, extended context, or partially completed code to help you get started. When working on a case study, keep both this PDF and Colab notebook open and use these references to move smoothly between the written materials and your code.

C.2.3

Coding Lab 1 — Web Scraping in R: step by step guide

Instructions: Work individually. Solve all exercises in the corresponding Colab notebook. Record your answers and/or code in your copy of the notebook, or in the format required by the instructor.

Notebook: Coding Lab 1

Case study G.2.1

Random variables in the wild: *Reddit* posts and empirical distributions

Instructions: Work in pairs or groups of three. Answer the questions

Notebook: Case Study 1

Dataset: aiwars.csv

One of you must share editor access to their notebook with the rest.

Scenario: We will cover this week's lecture contents using a real-world dataset from Reddit. You will put your data manipulation (with dplyr and base R) skills to practice

---

Context: The `AIwars` dataset consists of a collection of posts scraped from the `r/AIwars` subreddit, a forum where users debate the societal implications of AI. These range from predictions about AI-driven job loss and technological conflict to satire, trolling, and speculation. The dataset captures a rich period of discussion and polarization. Each observation corresponds to a single post, with information about its author, contents and engagement.

Key Variables:

- `post_index` — Unique identifier for each post (starts at 1 and consecutively numerates all posts).
- `author` — Reddit username of the post author (may be `[deleted]`).
- `post_date` — an R `Date`
- `fulltext` — Full text of the Reddit post in format `TITLE: [some post title] TEXT: [some post text]`
- `post_length` — the net number of characters in `fulltext` (excluding the TITLE and TEXT headers).
- `post_upvotes` — Number of upvotes (user endorsements or *likes*) the post received.
- `comments_number` — Total comments the post received (includes replies to other comments).

Part 1. Basic dataset facts

1.1 [1.1] Install and load the `tidyverse` packages. Create `aiwars_URL`, a `character` with the download URL for `aiwars.csv`. Then read in the dataset as `aiwars`, a data frame. Use `glimpse()` to answer:

(a) How many posts are we working with?
(b) How many variables does the dataset have?
(c) How many are *true* `character` types?
(d) How many are numeric?
(e) Which characters are better described as factors? Why?

1.2 [1.1.1] For the entire case study, will use only the **Key Variables** described above. While `select()`ing columns from the current data frame is possible, a memory-efficient alternative is to read in only those columns we need.
Use the `col_select` argument in `read_csv()` to create `aiwars_short`, a data frame containing only the columns described as **Key Variables**.

1.3 [1.1.2] Use `select()` to create `aiwars_short2`, a dataframe with only the **key variables**.

1.4 Moving forward we will work with `aiwars_short` only. You may delete `rm(aiwars, aiwars_short2)`.

1.5 Use `summary()` or other summarizing methods to answer the following questions:

   (a) What is the time span of the posts?
   (b) On average, how long (in words) is a post on this subreddit?
   (c) How many posts don't have any replies?
   (d) What is the largest number of upvotes in a post?
   (e) Which author has posted the most? (Consider `as.factor()`).
   (f) How many distinct users have posted in this subreddit? (Consider `unique()`).

Part 2. Counting posts

2.1 [2.1] Create the following variables in `aiwars_short`:

   (a) `popular`, takes value 1 when the post has 29 or more upvotes. Takes value 0 when the post has less than 29 likes.
   (b) `text_classification`, which takes value `mostly title` if it is less than 70 characters long, `short` if it has 70 or more but less than 110 characters, `common` if it has 110 or more but less than 900 characters, and `long` if the post has over 900 characters.

2.2 How many `common` posts are there?

2.3 If we draw a post at random, it will be a popular one with what probability?

2.4 If we instead sample 10 posts at random **with replacement**, what is the probability 3 of them are popular?

2.5 [2.2] Suppose random variable X; $\Omega_X = \{0, 1, 2, ..., N\}$ represents the number of popular posts in $N = 10$ draws with replacement from `aiwars_short`. For the following probability statements describing various events, first write them down as a probability and then use R to compute them.

   (a) What is the probability of getting at most 4 popular posts?
   (b) What is the probabililty of getting at least one but at most 3?
   (c) What is the probability of getting a number of popular posts that is not 0 or 4?

2.6 Similarly, we can treat the texts' classification as random variable Y. Is it continuous or discrete? What is Ω_Y?

2.7 [2.3] Express $f_Y(y)$ as a data frame `f_Y` with as many rows as elements in

Ω_Y and two columns: `y`, the value taken by Y and `p` its mass or density.

2.8 What is the probability a post is not `mostly title` ?
2.9 What is the probability a post is either `common` or `long`?

Are popular posts different?

2.10 What is the probability a post is popular **AND** `long`?

As we learned from the lecture, if two events are **not independent**, the additional information one of them provides should *update* the probabiility of the other. We will examine this fact by calculating the probability of a post being long **GIVEN that we know it is popular**:

$$P(Y = long \mid popular = 1)$$

As a reminder:

$$P(long \mid popular = 1) = \frac{P(long \, \cap \, popular = 1)}{P(popular = 1)}$$

2.11 Use your answers to questions 2.3 and 2.10 to compute the probability a post is long GIVEN it is popular. How does this probability compare to the unconditional probabiity $P(Y = long)$?

2.12 We now know that the event $(Y = long)$ has two mutually exclusive and exhaustive partitions: $(popular = 1)$ and $(popular = 0)$. Following the lecture, Show that the Law of Total Probability verifies for this event.

2.13 What is $P(popular = 1 \mid long)$? Is your answer the same as in 2.11 ? Should it be? Why?

2.14 [2.4] Create `joint_pmf`, a data frame similar to the one you created for 2.7; in this case, it should display the probability for all possible values in $Y \cap Popular$. This is the ordered pair $\Omega_Y \times \Omega_{Popular} = (long, 1), (long, 0), ..., (\text{mostly title}, 1), (\text{mostly title}$

2.15 [2.4.1] Use `joint_pmf`, `p` (or $f_{popular}$) and `f_Y` to compute the following in R:
   (a) $P(Y \mid Popular = 1)$, a vector of length 4.
   (b) $P(Popular \mid Y = common)$. What is its length? .

14.310x Flipped Classroom
Week 3 Instructions

Some title

Checklist

- ☐ Complete Guided Case Study 2 (Sessions 1 & 2)
  - ☐ We will continue to work with `aiwars`
  - ☐ Get the `aiwars_embeddings` dataset here
- ☐ Complete Open Case Study 1 (Session 2)

Case study G.3.2

Analyzing text similarity:
language semantics and random variables

Instructions: Work on your own for Session 1, and in pairs or groups of 3 for Session 2.

Notebook: Case Study 2

Dataset: aiwars_embeddings.csv

Part 1 Part 2 Part 3

Dataset: speech_anchors.csv

Before we dive into this week's lecture concepts, you will apply your newly acquired skills by hard-coding vector operations, and iterating them through the rows of our dataset to later perform a *semantic similarity* analysis of the contents in the AIwars posts. We will work with joint and conditional PDFs, CDFs and marginal distributions of a pair of continuous random variables associated with the semantics, tone and topics of posts in `aiwars`.

To that end, we have prepared the `aiwars_embeddings` dataset (split into three parts for file-sharing purposes). It contains 1024 variables associated with each post's `fulltext`. You will learn what these embedding variables `V1`, `V2`, ..., `V1024` represent below, but keep in mind `post_index` in both datasets uniquely links each post in `aiwars` to its embedding in `aiwars_embeddings`.

`speech_anchors` is a 2-row data frame you will use for comparison later.

Part 0. Required data and packages

0.1 [0.1] Load/install the `tidyverse` and the `geometry` packages.
0.2 [0.1] Read in `aiwars`, the same dataset as last week. Also, read in `speech_anchors.csv` as `anchors`. This should be a data frame with two rows and 1025 columns.
0.3 [0.1] Read in parts 1,2 and 3 of `aiwars_embeddings` as `part1`, `part2`,`part3` respectively. Then use `rbind()` to vertically merge the parts into `aiwars_embeddings`. Optionally, use `arrange()` to sort the dataset in `post_index`- ascending order.

Scenario:

Natural Language Processing (NLP) focuses on enabling machines to understand and work with human language. One of the key advances in NLP has been the development of methods that represent text — such as words, sentences, or entire posts — as vectors. These vector representations, often referred to as *embeddings*, capture aspects of a text's semantic content: its meaning, tone, and topical focus.

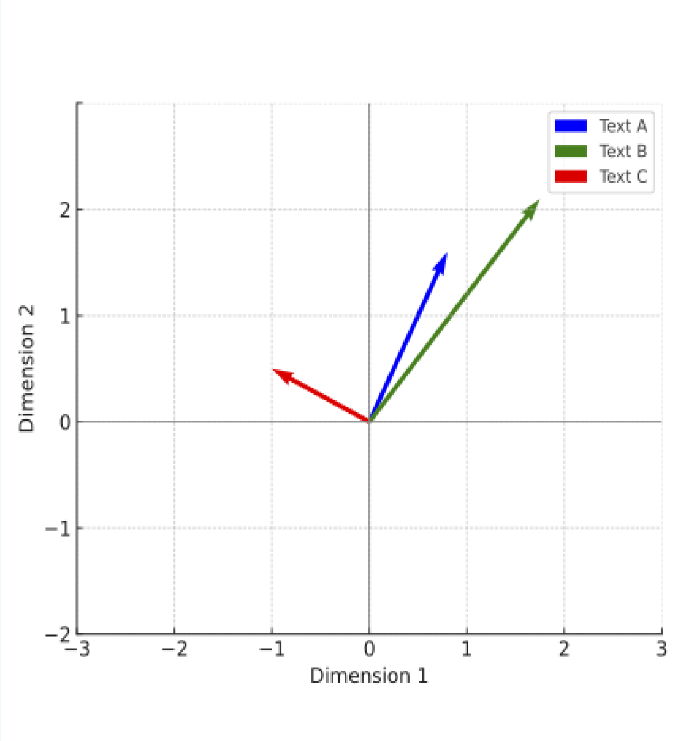
To illustrate the idea, suppose we have the following texts:

- Text A: "I love how these new AI tools can generate art!"
- Text B: "AI-generated images are cool, but I'm worried about copyright."
- Text C: "I painted this myself — no software involved."

We embed these texts in 2-dimensional vectors from the origin, plotted below:

- $\vec{a} = \begin{pmatrix} x_a \\ y_a \end{pmatrix} = \begin{pmatrix} 0.8 \\ 1.6 \end{pmatrix}$
- $\vec{b} = \begin{pmatrix} x_b \\ y_b \end{pmatrix} = \begin{pmatrix} 1.7 \\ 2 \end{pmatrix}$
- $\vec{c} = \begin{pmatrix} -1 \\ 0.3 \end{pmatrix}$

Figure 1: **2D text embeddings (vector from the origin)**



Despite their differences in tone, $\vec{a}$ and $\vec{b}$ in Figure 1 are close to each other because the texts they represent use AI-related language, whereas $\vec{c}$ is far removed given the lexical differences. But what exactly is meant by "close to each other"? There are two common ways to determine the semantic similarity between two embeddings: **direction** (i.e., the *angle* between them) and **distance**

Part 1A. Distance-based similarity

You will start by programming functions such as the *magnitude* of a vector, and the *distance* between two vectors. After a brief explanation, you will implement each of them in R.

Distance between two vectors

The distance from $\vec{a}$ to $\vec{b}$ in Figure 1 is defined as:

$$|| \, \vec{a}, \vec{b} \, || = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}$$

This is the sum of their x and y-coordinates' differences squared (in any order). Finally, we take the square root of that sum. Substituting the values in the scenario description:

$$\cdots = \sqrt{(0.8 - 1.7)^2 + (1.6 - 2)^2}$$

$$\cdots = \sqrt{0.81 + 0.16} = 0.985$$

1.1 [1.1] Save $\vec{a}, \vec{b}, \vec{c}$ as numeric vectors `a`, `b` and `c` respectively. Compute the distances for each pair of vectors and save them accordingly: `dist_ab`, `dist_ac`, `dist_bc`. Hint: you can apply operations on all the coordinates at once: `(a-b)`.

(a) Make sure your result for `dist_ab` is the same as above.

In general, to get the distance between any two n-dimensional vectors

$$\vec{V} = \begin{pmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{pmatrix}, \vec{U} = \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{pmatrix}$$

we generalize the process with all their coordinates and take the square root:

$$|| \vec{V}, \vec{U} || = \sqrt{(v_1 - u_1)^2 + (v_2 - u_2)^2 + \cdots + (v_{n-1} - u_{n-1})^2 + (v_n - u_n)^2}$$

$$\cdots = \sqrt{\sum_{i=1}^{n} (v_i - u_i)^2}$$

1.2 [1.2] `aiwars_embeddings` contains a 1024-dimensional vector per post. Program a distance function `dist_function(V, U)` that takes any two equal-length, numerical vectors. It returns the distance between them. If you didn't in the previous exercise, make sure to use vectorized operations (e.g., `sum()`, squaring all elements at once as $(a-b)^2$) to generalize the computation.

(a) Verify your function is correct and reproduce the results in 1.1

Distance from one, to multiple vectors

Working with individual, separate objects such as `dist_ab`, `dist_ac`, and so on can be difficult and tedious. In R, we will often want all the distances with respect to $\vec{a}$ in a single "distances" vector or variable:

$$D_a = \begin{pmatrix} || \vec{a}, \vec{a} || \\ \\ || \vec{a}, \vec{b} || \\ \\ || \vec{a}, \vec{c} || \end{pmatrix}$$

We will now pass `dist_function()` trhough all the example vectors at a time to obtain D_a — the steps should be familiar from the previous Coding Lab.

1.3 [1.2.1] Create vector `D_a` with a *for* loop by following the steps below:

- Declare `D_a`, an empty vector.

  - Use `rbind` to create `examples_matrix`, a matrix with 3 rows and 2 columns. One row for each example vector `a,b,c` and one column for each of their x, y-coordinates.
  - Declare a `for(...)...` loop with as many iterations as rows in `examples_matrix`.
  - Inside the *for* loop, code the following:
    - Subset `examples_matrix` to obtain vector `v`.
    - Obtain the `distance` between `a` and `v` with `dist_function`.
    - Use `append` to recursively add a `distance` on each iteration to vector `D_a`.

1.4 Verify your answers with those of 1.2. What should be the result for $||\vec{a}, \vec{v}||$when $\vec{v} = \vec{a}$? Why?

Finally, we can wrap the code we created for 1.3 in a function that directly returns D_a when given a vector and a matrix.

1.5 [1.2.2] Create a function `get_distances(u, M)` which takes a vector `u` of length n and a matrix `M` with an arbitrary number of rows k, and n columns. The function should `return` D_u, a vector of length k where each element is the distance between `vector` and a row of `matrix`.

1.6 Use `get_distances(_,_)` to reproduce 1.3. Verify it is the same vector.

The norm of a vector

The norm $|| \vec{V} ||$ (also called the *magnitude* or *length*) of a vector indicates how long the arrow is from the origin to the point it reaches. Since all embeddings are vectors at the origin (all their starting coordinates are 0), we can calculate this as the distance between a vector $\vec{V}$ and the n-dimensional zero: $||\vec{V}, \vec{0}||$.

$$|| \vec{V}, \vec{0} || = || \vec{V} || = \sqrt{(v_1 - 0)^2 + \cdots + (v_n - 0)^2}$$

$$\ldots = \sqrt{\sum_{i=1}^{n} v_i^2}$$

1.7 [1.3] Create `norm0_function`, a function that takes `V`, a numerical vector of length n as an input, and returns its norm from the origin. Hint: you can recycle `dist_function` inside `return()` with the appropriate `U`.

1.8 [1.3.1] Compute $|| \vec{a} ||, || \vec{b} ||$ and $|| \vec{c} ||$. Save them to `a_norm`, `b_norm`, `c_norm` respectively.

1.9 Similar to 1.3 and 1.5, create a function `get_norms0(M)` taking a matrix of n rows/vectors, all with the same number of dimensions/columns m, and returns a vector N_0 of length n with a norm from the origin for each row/vector in `M`. Input it the `examples_matrix` and verify your results in 1.8.

Part 1B. Direction-based: cosine similarity

Distance conflates **direction** and **magnitude**: two vectors can be far apart in terms of distance even if they point in exactly the same direction, simply because one is much longer than the other. A complementary approach is to compare direction only, through the angle θ formed by two vectors. The cosine of said angle

$$cos(\theta) = \frac{\vec{a} \cdot \vec{b}}{|| \, \vec{a} \, || \;\; || \, \vec{b} \, ||}$$

1. Their **difference in direction** measured by the shortest angle θ between them. However, for interpretability purposes, the cosine of said angle $cos(\theta)$ is used instead; this metric is referred to as **cosine similarity**. The cosine of θ is always a number between -1 and 1, where:
   - $\mathbf{cos}(\theta) = \mathbf{1}$ means the angle is $\theta = 0°$, indicating identical semantic direction (not identical text, as these could be different in magnitude, for instance).
   - $\mathbf{cos}(\theta) = \mathbf{0}$, the angle is $\theta = 90°$, indicating the posts are, for the most part, semantically unrelated: different topics, tone and word choice.
   - $\mathbf{cos}(\theta) = \mathbf{-1}$, with angle $\theta = 180°$, vectors point in opposite directions, indicating they are semantically adverse (e.g., an example for text A could be *"I hate how AI tools are destroying real art and replacing human creativity"*).

Part 2. Processing speech

Explaining that **real** embeddings have more than a few dimensions. This one has 1024 exactly. Explain we obtained them from OpenAI's API/products (provide the link to this embedding's overview)
.... These numbers come from a model that captures the post's *meaning*. Posts with similar ideas will have similar embeddings. We won't worry about how they are built — just know they express meaning in this many dimensions and that no dimension has a clear human-interpretable meaning.
Exercise 1. Get the norms of aiwars_embeddings. Make them realize they're all normalized to 1.
Ex 2. Draw a few textual, funny examples from aiwars; have them be aware of the relationship between aiwars and aiwars_embeddings — they'll get their embeddings via the index in aiwars. Make them compute cosine and distance similarity between them.
—
For the last part, explain that after some pre-processing we came up with 2 anchors. Explain each anchor: "AI-aware", and "anti-nuance"; decribe some post characteristics when similar/dissimilar.
Have them compute cosine and distance-based similarities for these 2 anchors on the dataset. Manually examine a few posts. Finish this case study here. Next one about the statistics of the cosine similarity, pdfs, marginals, etc on the joint density.

Case study O. 3. 1

Instructions: Work in pairs or groups of three. Share a Colab Notebook where you previously load `cos_post1`, `cost_post2` and the `aiwars`. Create a deck with a minimum of 10 and a maximum of 15 slides, and a minimum of 4 summarizing plots to answer the following questions:

Scenario: We previously examined the cosine similarity of AIWars to two "gold standard" posts (a and b) in isolation — thinking of these similarities as continuous random variables that capture how close in meaning a given post is to each extreme.

In this case study, you'll explore how these semantic similarities relate to the the rest of variables we examined for `aiwars` : post length, popularity and activity. You will use the summarizing tools and the concepts of conditional, cumulative and marginal probability covered in the lecture to give graphical, general answers to questions on these relationships.

What can we learn abo when we condition on a post's length or number of comments?

Questions

14.310x Flipped Classroom

Week 4 Instructions

Some title

Checklist

- ☐ Complete Coding Lab 4 (Sessions 1 & 2).
- ☐ (Optional) Explore the **Review Notes** and further **Readings** available.

Coding lab L.4.4

Understanding Probability and Statistics in R: A Step-by-Step Guide

Instructions: Work individually. Answer all questions in sections 1-6. Sections 7 and 8 are optional; follow your instructor's directions.

Notebook: Coding Lab 4

Record your answers in your copy of the notebook, or in the format required by your instructor.

Additional resources

– **Drive: Review Notes**

- – **Drive:** Readings

14.310x Flipped Classroom

Week 6 Instructions

Some title

14.310x Flipped Classroom

Week 7 Instructions

Some title

Checklist

- ☐ Set aside this Wikipedia article on testing two-proportions hypotheses, in case you need it during Session 2 (Requirement)
- ☐ Skim this Wikipedia article discussing the Local Average Treatment effect (LATE) , in advance of Session 2. (Requirement)
- ☐ Complete Guided Case Study 3 invidually (Session 1)
  - ☐ Retrieve the `students` dataset here
- ☐ Complete Open Case Study 2 in pairs or teams of 3. (Session 2)
  - ☐ You will continue to use `students`

Case study G.7.3

Evaluating AI-assisted learning on student outcomes

Instructions: Work on your own; read the scenario and answer the questions. Type your answers in the format required by the instructor.

To work on the `students` dataset you may use either a Colab notebook or your own installation of R.

Dataset: students.csv

Your code will not be evaluated, but keep your R script or notebook tidy, as you may need to review some of your answers during Session 2.

Scenario:

You are the Government of *Novaria*'s new Minister of Education. The Prime Minister has tasked you with evaluating a primary education policy recommendation: the rollout of AI-assisted learning for mathematics curricula in grades 5-8.

The proposed program, *Project Mentor*, involves deploying a large language model (similar to ChatGPT) named *AlgebrAI* specifically trained and fine-tuned for elementary math tutoring. AlgebrAI's interface is tailored to deliver interactive, one-on-one tutoring sessions to students. The AI mentor adapts to each student's skill level and provides problem-solving guidance, hints, and feedback designed to help the students master their grade's math curriculum.

Each participating school receives a number of tablets with AlgebrAI pre-installed, configured for offline-first use and automatically synced with central servers when internet is available. Students selected for treatment attend 20-minute tutoring sessions per day under the supervision of a facilitator.

The Prime Minister believes Project Mentor can boost test scores nationwide, but political opponents have raised concerns over cost and long-term efficacy. You are now in charge of evaluating the impact of the program in grades. Your team provides you with:

1. A 6th-grade math test designed to perfectly measure domain of the curriculum in a scale from 0 to 100.
2. A list of 1,000 students enrolled in 6th grade across Novaria, picked at random — part of the `students` dataset. This list contains only the following variables:
   - `unit`: a consecutive number assigned to the student.
   - `W_school`: Indicates whether the student's school is managed by the government ($W_{school} = 1$) or if it is privately managed ($W_{school} = 0$)

You have authority to apply the exam to any 6th grader in Novarnia, and you can implement the program (tablet usage and monitor time) in all government-managed schools, but to include any students attending a private school to the program you must first obtain authorization from their school board.

Exercises

Consider $T_i \in \{0, 1\}$ the treatment status of student $i = 1, 2, ..., 1000$ — $T_i = 1$ if treated $T_i = 0$ if not treated. Potential outcomes $y_i(T_i)$ in `students`, measured in test results (grades 0 to 100) are defined:

- `y0`: vector $Y(0)$, assume we can't observe it unless specified.
- `y1`: vector $Y(1)$, assume we can't observe it unless specified.

1.1 What is the value of $y_3(1)$? Describe its meaning —in terms of the potential outcomes framework.
1.2 What is the value of $y_5(0)$? Describe its meaning.
1.3 Compute $\bar{Y}(1)$. Describe its meaning.
1.4 Suppose $T = 0$. What is the value of y_{20}^{obs} and y_{40}^{miss} ? Briefly explain why.
1.5 Suppose $T_i = 1$ for all $i = 1, 2, 3, ..., 1000$. What is $\bar{Y}^{obs}$?
1.6 Imagine you can observe both potential outcomes.
   (a) What is the causal effect of Project Mentor in student 245?
   (b) What is the estimated Average Treatment Effect (ATE) of Project Mentor?
   (c) Does the estimated ATE support the Prime Minister's claims?

In practice, only Y^{obs} will be available after applying the exam. You will observe **one test score per student**, as well as the students' treatment status: either treated or untreated.

After careful consideration, your team assigned N_0 students to control and N_1 students to treatment out of the $N_0 + N_1 \equiv N = 1000$ sampled. The assignment criteria included logistics, the school-year timeline, operation costs and potential political opposition. Treatment was allocated amongsts students per the rule

$$T = W_{school}$$

2.1 Explain the assignment rule in simple words
2.2 For each of the assignment criteria, provide a brief circumstance that likely motivated Novaria's government to conclude this was the best allocation.
2.3 What is the value of N_0?
2.4 What is the value of N_1?
2.5 Create a variable for $Y^{obs}(W)$, and name it `yobs_w`. With this variable:
   (a) Compute the value of $\bar{Y}^{obs}(1)$.
   (b) Compute the value of $\bar{Y}^{obs}(0)$.
2.6 Write down both expressions $\bar{Y}^{obs}(\cdot)$ more formally, in terms of summations.
2.7 Your team knows that $ATE = E(y_i^{obs}|W = 1) - E(y_i^{obs}|W = 0)$ but they don't know why, or how to estimate it from our sample.
   (a) What is $\widehat{ATE}$?
   (b) Justify your answer in terms of a famous mathematical theorem:
      i. $\square \xrightarrow{\square} E(y_i|W = 1)$
      ii. ...
      iii. Therefore the estimate ...
   (c) Compute $\widehat{ATE}$ using R.
   (d) **Reflect on the result**. How does it compare to your answers in 1.6b and 1.6c? At this point, do we have any way to diagnose the accuracy of this result?
2.8 Again, let's imagine we can observe potential outcomes. In the lecture, it was shown that the ATE can be decomposed in *treatment on the treated* and *selection bias*. Write down that expression and estimate the values of:
   (a) treatment of the treated
   (b) selection bias

(c) each individual term in *selection bias*

2.9 What do these values imply for the experiment's design? Is the value for 2.8a a potentially good $\widehat{ATE}$? What would be omitted if we were to only consider this value?

Case study O.7.2

Evaluating AI-assisted learning on student outcomes (continued)

Instructions: Work in pairs or groups of 3; answer the questions as concisely as possible. Type your answers in a single shared document or in the format required by the instructor.

One of you must set up a blank Colab notebook to work on, and share it with the rest. Save any figures or output, and incorporate as required by the instructor.

This is a direct continuation of G.7.3, thus we will work under the context you already have. Continue to use `students` when necessary to answer the questions.

Scenario: You let the Prime Minister know the treatment allocation for the Project Mentor experiment you had previously agreed on is problematic. He hires a team of consultants to help you sort this design problem out, as well as polish other details of the experiment. The following exercises are contain some of the questions asked during the meetings held with the consulting team and the Prime Minister.

Meeting 1

1.1 Firstly, you are asked to explain generally why you cannot get a credible average treatment effect from the current treatment allocation. How would outcomes be different we were to scale up the program nationally? (use your "secret" knowledge of the potential outcomes)

1.2 You are asked to provide an alternative assignment that would create two groups equally representative of 6th-graders nationally. Create such assignment variable under the name `T`, and also create `yobs_t`, the outcome we would observe under this assignment. Calculate the $\widehat{ATE}$. How does this result compare to 2.8a in G.7.3? Without making any further calculations, what do you think the treatment effect among private schoolers will be?

1.3 The Prime Minister doesn't believe that your new assignment created comparable groups. One way to provide evidence of balance, is showing the groups have the same composition of public and private schoolers. Formally show there is no evidence to reject the composition is the same. Be as conservative as possible with the variance.

1.4 Imagine everyone can observe potential outcomes. From the definition of ATE, show treatment and control are comparable more decisively.

Meeting 2

While more convinced of your new assignment, the Pime Minister still insists asking for permission to private schools is impractical and will delay matters. Conveniently, the consulting team asks two questions:

- Whether attending a private/public school in Novartia actually creates systematic differences between students; particularly, differences related to the outcome. This has not been formally shown.
- Whether there may be differences in treatment effects between public and private students (e.g. the mean effect is larger for any), as these differences would justify different rollouts.

To provide evidence in favor or against these questions, bear in mind we have to start from the following assumption:

$$y_i(0)|W = 0 \sim Distr(\mu_0,\ \sigma^2_{0,0})$$
$$y_i(1)|W = 0 \sim Distr(\mu_1,\ \sigma^2_{1,0})$$
$$y_i(0)|W = 1 \sim Distr(\nu_0,\ \sigma^2_{0,1})$$
$$y_i(1)|W = 1 \sim Distr(\nu_1,\ \sigma^2_{1,1})$$

Where $\sigma^2_{0,0} \neq \sigma^2_{0,1} \neq \sigma^2_{1,0} \neq \sigma^2_{1,1}$

2.1 In your own words what do these assumptions mean? What do they entail when it comes to testing hypotheses? According to the lecture, what should we assume about the correlation among these random variables if we want to be conservative?

2.2 Answer the question about systematic differences in outcomes between public and private schools with the evidence you have.
   (a) State the appropriate null hypotheses and their alternates.
   (b) Test them with the appropriate statistic (estimate any parameters you don't know).
   (c) Tie your conclusions directly to the question with 95% confidence.

2.3 Answer the question about differences in treatment effects.
   (a) State the appropriate null hypotheses (test equality).
   (b) Make inference on $\hat{\nu}_1, \hat{\nu}_0, \hat{\mu}_1, \hat{\mu}_0$ accordingly.
   (c) Tie your conclusions directly to the question with 95% confidence.

Meeting 3

Satisfied with your answers, the Prime Minister and consultants approach you with some final questions about the program's broader implications:

3.1 **SUTVA violations** In your own words, briefly explain the Stable Unit Treatment Value Assumption (SUTVA). Could implementing Project Mentor violate this assumption in Novaria? Provide a specific scenario illustrating such a violation clearly. How might these externalities affect the accuracy of your estimates?

3.2 **Alternative policies with proven outcomes (e.g. TaRL)** The consultants suggest evaluating cheaper alternatives, like Teaching at the Right Level — targeting teaching to each student's current skill level without advanced technology; human mentors, complementary material, smaller traditional groups (more teachers), among others. These alternatives currently have more robust evidence of their effects.

(a) What, if any, are some differences between the theory of change underlying TaRL and that of Project Mentor?

(b) If differences exist, briefly discuss how you would test them within an experimental design, clearly describing treatments, assignment and measured outcome(s).

(c) Apart from the treatment effects, what else is necessary if we wanted to fairly compare any known TaRL intervention to Project Mentor in terms of efficiency?

(d) In this comparison, how important do you think scale would be? Briefly describe how costs for one and the other would behave.

3.3 **Non-compliance** Not every school or student may strictly follow the treatment assignment. Describe one realistic scenario of non-compliance in this project. Explain briefly how such non-compliance might bias the estimated treatment effect. Suggest one practical strategy to reduce or mitigate non-compliance.

14.310x Flipped Classroom
Week 8 Instructions

Some title

Checklist

- ☐ Watch the linear models with R: `lm` tutorial[4] (Requirement)
- ☐ Complete Guided Case Study 4 (Session 1)
  - ☐ Get the `bike_rentals` dataset here
- ☐ Complete Guided Case Study 5 (Session 2)
  - ☐ Get the `student_performance` dataset here
- ☐ Complete Guided Case Study 6 (Session 2)
  - ☐ Get the `kc_house_data` dataset here
- ☐ (Optional) Explore **Review Notes** and further **Readings** available.

---

[4] **Module 8 > Introduction to the Class lm** in the online component of the course.

Guided case study G.8.4

Part A - Bike rentals

Instructions: Work in pairs or groups of three. Solve the exercises for Part A of *Linear Regression* in Colab. Work collaboratively in a single Notebook.

Notebook: Part A

Dataset: bike_rentals.csv

Type your answers in the notebook, and submit your work per the instructor's requirements.

Guided case study G.8.5

Part B - Student performance

Instructions: Work in pairs or groups of three. Solve the exercises for Part B of *Linear Regression* in Colab. Work collaboratively in a single Notebook.

Notebook: Part B

Dataset: student_performance.csv

Type your answers in the notebook, and submit your work per the instructor's requirements.

Guided case study G.8.6

Part C - KC Housing Data

Instructions: Work in pairs or groups of three. Solve the exercises for Part C of *Linear Regression* in Colab. Work collaboratively in a single Notebook.

Notebook: Part C

Dataset: kc_house_data.csv

Type your answers in the notebook, and submit your work per the instructor's requirements.

Additional resources

- **Drive: Review Notes**
- **Drive: Readings**

14.310x Flipped Classroom
Week 9 Instructions

Some title

Checklist

- ☐ Complete Coding Lab 5 (Session 1)
- ☐ Complete Guided Case 7 (Session 2)
- ☐ Review the reference material as needed (Optional)

Coding Lab C.9.5

Coding Lab 5— Further regression tools

Instructions: Work individually. Complete all the coding lab's exercises.

Notebook: Further regression tools

Upon completion, submit your work in the format required by the instructor.

Guided Case Study G.9.7

Regression Discontinuity: Replicating *Going to a better school* (Pop-Eleches & Urquiola, 2013)

Instructions: Work in pairs or teams of three. We will go over a section of *Going to a better school: Effects and Behavioral Responses* to examine outcomes differences of children attending higher achievement schools.

- **Notebook:** **Guided Case 7— RDD paper replication**
- **Dataset:** **Schools.dta**
- **Paper:** **(Pop-Eleches & Urquiola, 2013)**

Scenario: In 2002, the Romanian Ministry of Education centralized the high school admissions system, ranking students by their standardized test scores and matching them to schools in descending order of achievement. This reform generated a compelling natural experiment: some students who barely made it into higher-achieving schools were nearly identical, academically, to those who just missed the cutoff. In this guided case study, you will analyze data from this setting to investigate whether attending a better school causally affects student outcomes. You'll explore the design of the regression discontinuity strategy used by Pop-Eleches and Urquiola (2013), and replicate parts of their analysis using real admissions and outcomes data from Romanian high schools.

A Colab notebook has been set up with the full case directions therein. Submit your coursework in the format required by your instructor.

Additional materials and references

References:

Drive:

- (Pop-Eleches & Urquiola, 2013)
- Causal inference textbook
- Econometrics textbook

Additional materials:

Drive:

- Review notes week 9

Bibliography

Pop-Eleches, C., & Urquiola, M. (2013). Going to a better school: Effects and behavioral responses. *American Economic Review*, *103*(4), 1289–1324. https://doi.org/10.1257/aer.103.4.1289